Artificial Neural Networks Modeling of Total Dissolved Solid in the Selected Locations on Tigris River, Iraq

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ABSTRACT

The study aims to predict Total Dissolved Solids (TDS) as a water quality indicator parameter at spatial and temporal distribution of the Tigris River, Iraq by using Artificial Neural Network (ANN) model. This study was conducted on this river between Mosul and Amarah in Iraq on five positions stretching along the river for the period from 2001to 2011. In the ANNs model calibration, a computer program of multiple linear regressions is used to obtain a set of coefficient for a linear model. The input parameters of the ANNs model were the discharge of the Tigris River, the year, the month and the distance of the sampling stations from upstream of the river. The sensitivity analysis indicated that the distance and discharge have the most significant affect on the predicted TDS concentrations. The results showed that a network with (8) hidden neurons was highly accurate in predicting TDS concentration. The correlation coefficient (r), root mean square error (RMSE) and mean absolute percentage error (MAPE) between measured data and model outputs were calculated as 0.975, 113.9 and 11.51%, respectively for testing data sets. Comparisons between final results of ANNs and multiple linear regressions (MLR) showed that the ANNs model could be successfully applied and provides high accuracy to predict TDS concentrations as a water quality parameter.

نمذجة الشبكات العصيبة الاصطناعيه للاملاح الذائبة الكلية في مواقع مختارة من نهر دجلة في العراق

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المقدمة

تهدف الدراسة الى التنبؤ بتراكيز المواد الصلبه الكلية (TDS) بوصفها مؤشرا لنوعية المياه تبعا التوزيع المكاني والزماني لنهر دجلة في العراق باستخدام نموذج الشبكه العصيبة الاصطناعية (ANN).اجريت الدراسة لخمسة مواقع على طول نهر دجلة بين الموصل والعمارة في العراق للفترة (2001- 2011).لمعايرة نمذجة الشبكه العصيبه الصناعية تم استخدام برنامج الانحدار الخطي المتعدد للحصول على مجموعة من المعاملات للنموذج الخطي.ان المدخلات الاساسيه للمتغيرات الداخله لبرنامج (ANNs) هي تصريف النهر، السنة، الشهر، المسافة لمواقع المحطات من مقدم النهر.أظهر تحليل الحساسيه ان المسافة والتصريف لهما تاثيرجوهري على توقعات تراكيز (TDS). بينت النتائج ان الشبكة ذات ثمانية عقده في الطبقه المخفيه (hidden layer) من الخلايا العصيبة كانت دقيقه للغاية للتنبؤ في تركيز (TDS).ان قيمة معامل الارتباط (r) وجذر متوسط مربعات الخطأ (RMSE) ومعدل نسبة الخطأ المطلق (MAPE) بين البيانات المقاسة والبيانات التي تم حسابها من النموذج كالآتي(0.975، 113.9، 11.51%).أشارت نتائج المقارنة النهائية لنموذج الشبكات العصيبة الاصطناعية (ANNs) مع الانحدار الخطي المتعدد (MLR). ان نموذج (ANNs) يمكن ان يطبق بنجاح ويوفر دقة عالية لتنبؤ تراكيز (TDS) كمؤشر لنوعية المياه.

Keywords: Tigris River , TDS, ANNs, and discharge.

1-INTRODUCTION

River water quality is a significant concern in many countries, considering agricultural and drinking consumptions. Therefore, prediction of TDS as the main water quality condition is a necessary tool for water resources planning and management. Limited water quality data and the high cost of water quality monitoring often pose serious problems for process-based modeling approaches .Artificial Neural Networks (ANNs) provide a particularly good option, because they are computationally very fast and require many fewer input parameters and input conditions than deterministic models, ANNs, however require a large pool of representative data for training **,Ali , et al., 2009.**

In recent years, ANNs have been successfully applied in the area of water quality modeling. The use of ANN model was to be better than other simulations and commonly used statistical models **,Mas and Ahlfeld, 2004.** due to the complex interrelated and non-linear relationships between multiple parameters. ANNs have been used successfully for predicting TDS parameter in streams, river and lakes, **,Kanani et al., 2008. ,Ali et al., 2009. ,Abudu et al., 2011. ,Asadollahfard et al., 2012. ,Moasheri et al., 2013. and ,Nemati et al., 2014.** There have been a number of studies for Iraqi researchers on the Tigris River water quality modeling, especially within Mosul and Baghdad, with some examples: **,Al Shami, 2006. ,Abudl Razzak, et al., 2009. ,Abed and Ismail, 2013. ,Al-Suhaili, and Ghafour, 2013. , Ali,S.M.2014. ,Ismail et al., 2014. ,Kadhem,2014. and ,Flaieh et al., 2014.** Over the last few years. Few studied have been conducted to predict some water quality parameters on Iraqi Tigris River by using ANNs model. These studies have demonstrated some degree of success, **,Al-Suhaili et al., 2008. and ,Al-Suhaili, and Mahammed, 2014.**

The water quality of the Tigris River, using the parameter TDS as an indicator water quality is varying from place to place along the river and overtime. Water salinity, expressed as TDS, is an increasing problem in Iraq. Salinity increases as the river water flow southward and evaporation, sewage effluent dissolution of limestone and agricultural drainage **,Al Marsoumi et al., 2006.** However, TDS values of the Tigris water at the Turkish Iraqi border are 280 mg/l and the River reaches more than 1500 mg/l at Amarah, Iraq **,Al-Ansari, 2013.** The main objectives of this study are to predict the spatial and temporal changes in TDS parameter throughout the selected sampling stations on the Tigris River using ANNs model.

2- MATERIALS AND METHODS

2-1 Data and Site Description

The Tigris River is one of the most important twin rivers in Iraq, 1850 km long. The total length of the river in Iraq is 1415 km with a catchment area of 235000 km^2. Hydrological behavior of the Tigris River has been changed due to the construction of large dams and irrigation projects in Turkey and Iraq. The Tigris River mean discharge at Mosul city prior to 1984 was 701 m^3/sec and dropped to 596 m^3/sec afterward. This implies that 15% of the river discharges were been decreased. The average discharge in Baghdad was 544 m^3/sec. This value is far away from the mean daily flow prior to 2005 , 1140 m^3/sec **,Ali et al., 2012.** On the other hand, discharges south of Baghdad reduced in the Tigris to 37 BCM at Kut . Past Kut, the Tigris supplies water for irrigation and public water supply and also discharge to the central marsh combined .These discharges reduced

3 BCM at Qalatsalih during the period after 1990 , **,ESCWA-BGR, 2012.** In the present study, ANNs model was applied for TDS water quality parameter of five sampling stations on the Tigris river (Mosul in the north of Iraq, Samarra barrage, Muthanna bridge at Baghdad, Kut barrage and Amarah south of Iraq as shown in **Fig.1**. These data were collected from the **,National Center for Water Resources Management, Ministry of Water Resources, Iraq ,2012.** Water quality stations along the Tigris River are located between 36˚20.802′Latitude and 43˚08.417′ Longitude at Mosul, North of Iraq and 31˚51.338′Latitude and 47˚08.618′ Longitude at Amarah, South of Iraq. The ANNs model inputs are the monthly discharge (Q) in m^3/sec, distance (D) in m of the sampling station from the upstream of the Tigris river at Mosul, the year (Y) and the month of the data (M) . The output of the model was TDS as a water quality parameter. The data set has a record length of (11) years covering between 2001 to 2011 based on existing measured values of different variables. The average annual discharge of the selected stations along the Tigris River is shown in **Fig.2**. Also the average recorded annual TDS concentration is shown in **Fig. 3**.

2-2 Overview Artificial Neural Networks

Artificial Neural Networks (ANNs) are a flexible mathematical structure that is capable of identifying a large number of simple processing elements that are called neurons. The basic structure of an ANNs model usually comprised three distinctive layers, the input layer that all data are imported to the network and calculation the weight of each input variables are done; the hidden layer or layers, where data are processed; and the output layer, where the results of ANNs are produced .The number of neurons in the input hidden, and output layers depends on the problem. If the number of hidden neurons is small, the network may not have sufficient degrees of freedom to learn the process correctly. On the other hand, if the number is too high, the training will take a larger time and the network may over-fit the data **,Karunanithi et al., 1994.** Many authors have described the structure and operation of ANNs **,Zurada, 1992.** The most common activation function is sigmoid (logistic) function and is described as follows, **,Diamantopoulos et al., 2005.**

$$f(x) = 1 / 1+e^{-x} \qquad (1)$$

2-3 Pre-processing and Data Division

It is a common practice to divide the available data into three sets, training, and validation. In this study, we randomly divide up the 100% of the target time steps into 80% for training and 20% for validation. The training data are further divided into 70% for training set and 30% for the testing set. The training set is used to adjust the connection weights of the neural network.

The testing set is used to check the performance of the network at various stages of learning, and training is stopped once the error in the testing set increases. The validation set is used to evaluate the performance of the model once training has been successfully accomplished. The way data are divided can have a significant effect one model performance **, ,Al-Janabi, 2006.** and trial – and – error process was used to select the best division .The data base used for the ANNs model comprises total of (660) individual cases .Missing data were found in each of the water quality sampling stations

.Ranges of the data used for the input and output variable are tabulated in **Table. 1**. Data pre-processing can have a significant effect on the generalization performance of a supervised neural network **,Dogan et al., 2009.** Normalization and transformation data was scaled or normalized using Eq. (2)

$$x_{scaled} = (x_{\circ} - x_{min}) \;/\; (x_{max} - x_{min}) \tag{2}$$

Where $x_{\circ}$ is the original data point, x_{min} and x_{max} are the minimum and maximum values in the data set, respectively. This is done in order to ensure that the min. value in the data set is scaled to zero, and the maximum value is scaled to one, **,Martin and Mohammad, 1994.**

2-4 Performance Evaluation and Modeling Error

The performance of model was evaluated by calculating the following statistical parameter: correlation coefficient (r), root mean square error (RMSE) and mean absolute percentage error (MAPE) defined by Eqs. (3-5), respectively

$$r = \frac{\sum(Q^0 - M^0)(QP - MP)}{\sqrt{\sum(Q^0 - m^0)2 \sum(QP - MP)2}} \tag{3}$$

$$RMSE = \frac{1}{N}\sum(Q_{\circ} - Q_p)^2 \tag{4}$$

$$MAPE = \frac{1}{N}\sum |Q_{\circ} - Q_p| \tag{5}$$

Where $Q_{\circ}$ and Q_p are the observed and estimated concentrations at the time steps, $M_{\circ}$ and M_p are the mean of the observed and estimated concentrations, respectively, and N is the total number of observations of the data set. The RMSE and MAPE measure the errors –however, RMSE is the most popular measure of errors which receives much greater attention than small errors. **,Sabah and Ahmed, 2011.** studied that the MAPE around 30% is considered a reasonable prediction.

Neural Network Model Application

Using the default parameters of the ANN model (0.2 for learning rate and 0.8 for momentum rate), a number of network with different numbers of hidden lager nodes (1-10) and with different transfer functions were developed. However the number of hidden unit directly affects the performance of the network. The best performance of these networks was with (8) hidden layer nodes and minimum values of correlation coefficient, RMSE and MAPE , **Table 2.** The best transfer functions for the input, hidden and output layers were linear, tanh and sigmoid respectively more than 150 trials were used in this study. The effect of the internal parameters controlling the back – propagation (momentum and learning rates) on model performance is investigated for the model with eight hidden layer nodes, **Table 2.** .The effect of the learning and momentum rates on the model performance is shown in **Figs.4** and **5**. Different values of learning and momentum rates were used, **Table 2**. It can be seen that the performance of the ANNs model is relatively sensitive to learning rates in the range (0.1 – 0.8) then the prediction errors increase sharply to (133.4), **Fig. 4** . **Fig. 5** shows the effect of the momentum rate on model performance. It can be seen that the performance of the ANNs model is relatively sensitive to momentum rate value of (0.8). The optimum values for learning and momentum rate used are 0.4 and 0.8, respectively .The coefficient of correlation, RMSE and MAPE were 0.975, 113.9 and 11.51%, respectively. Also, the network with (8) hidden layer nodes has the lowest prediction error for the training and validation tests. However, it is believed that network with (8) hidden layer nodes is considered optimal, Fig. (6).

The statistics of the training, testing and validation sets for the ANN models is shown in **Table 3**.The statistical parameters considered include the maximum, minimum, mean and standard deviation. To examine how representative the training, testing and validation sets are with respect to each other t-test and F-test are carried out. The t-test examines the null hypothesis of no difference in the means of two data sets and the F-test examines the null hypothesis of no difference in the variances of the two sets. For a given level of significance, test statistics can be calculated to test the null hypotheses for the t-test and F-test respectively. Traditionally, a level of significance equal to 0.05 is selected. Consequently, this level of significance is used in this research. This means that there is a confidence level of 95% that the training, testing and validation sets are statistically consistent. The results of the t-test and F-tests are given in **Table 4**. These results indicate that training, testing and validation sets are generally representative of a single population.

3- RESULTS AND DISCUSSION

The ANNs model was then adopted to simulate total dissolved solid (TDS) with respect to discharge of the selected sites along the Tigris River and time .It used ANNs architecture with one hidden layer (eight nodes) and with different activation functions . The optimum learning rate of 0.4 and momentum of 0.8 were selected by many trials, as explained above.

The sensitivities of above parameters for the TDS prediction were estimated by using **,Garson, 1991. and ,Goh,A,1995.** methods .ANNs connection weights were used in these methods, **Table 5**. The results indicate that the distance and discharge had the a significant effect on the predicted TDS with a relative importance of 58% and 27% , respectively , followed by year and month with a relative importance of 12% and 3% , respectively , **Fig. 7** .The minimum value of relative importance for the month variable is due to the water resources monitoring and management .There are no monthly variations in flow rates from barrages the regulators along the Tigris River as in the flow hydrograph . The developed ANNs models accurately simulated the water quality (TDS) of Tigris river .Typical ANN's prediction model results are TDS concentrations, for the total data (r=0.96), **Fig.8**. Comparison of simulated water quality in Tigris river is shown in **Fig.9** .There is no trend in increasing of TDS concentration in sampling site between Mosul and Samarra sites. The progressive increase in TDS concentrations was directly proportional with distance after Samarra to Kut sites but with low positive slope and high or sharp positive slope for Kut to Amarah sites. This is due to the effects of upstream developments drainage project, direct sewage disposal into the river and agricultural activities. Using the connection weights and the threshold levels which obtained from ANN model, **Table 5.** the predicted TDS concentration in (mg/l) for Tigris River can be expressed as follows:

$$\mathbf{TDS} = 146 + \frac{\mathbf{2832}}{\mathbf{1}+e^{(\mathbf{0.58+2.39\tanh(}x\mathbf{1)+1.84\tanh(}x\mathbf{2)+4.65\tanh(}x\mathbf{3)-8.83\tanh(}x\mathbf{4)-2.11\tanh(}x\mathbf{5)-3.06\tanh(}x\mathbf{6)+2.40\tanh(}x\mathbf{7)-2.57\tanh(}x\mathbf{8)})}} \quad \ldots\ldots\ldots(6)$$

Where:

$x_1 = 64.37 + 46.12*10^{-4}Q + 0.07\ M – 3.62*10^{-3}D – 0.033\ Y$ (6-a)

$x_2 = 19.48 – 12.27*10^{-4}\ Q + 0.11\ M – 2.31*10^{-3}D – 9*10^{-3}\ Y$ (6-b)

$x_3 = 264.44 + 3.88\ *10^{-4}\ Q + 0.61\ M + 4.87*10^{-3}D – 0.13\ Y$ (6-c)

$x_4 = 1889.86 + 5.11*10^{-4}\ Q + 0.27\ M + 14.12\ *10^{-3}D – 0.95Y$ (6-d)

$x_5 = 291.38 + 47.15*10^{-4}Q + 0.12\ M – 5.75*10^{-3}D– 0.15\ Y$ (6-e)

$x_6 = -74.93 - 7.13*10^{-4}Q - 0.6\ M + 1.0*10^{-3}D + 0.4\ Y$ (6-f)

$x_7 = -576.14 – 2.12*10^{-4}Q + 0.14\ M – 13.11*10^{-3}D – 0.29\ Y$ (6-g)

$x_8 = -13.10 - 7.03*10^{-4}Q + 0.33\ M – 6.13*10^{-3}D + 0.07\ Y$ (6-h)

It should be noted that Eq.(6) is valid only for the range of value of (M, Y, D, and Q) given in **Table 1**. This is due to the fact that ANN should be used only in interpolation and not extrapolation **,Tokar, and Johnsn, 1999.** Eq. (6) is long and complex because it contains four independent variables. On the other hand, it can predict accurately the TDS of Tigris River as shown in **Fig. 8** with a correlation coefficient equal to 0.96 and value of MAPE less than 30% . The equation length depends on the number of nodes in the input and hidden layers. A neural network of four input neurons, eight hidden neurons and one output is found to be the optimum architecture for the current problem as shown in **Fig. 10**.

Multiple linear regression (MLR) may be viewed as a special case ANNs model that uses linear transfer functions and no hidden layers, if the linear model performs as a basis for comparison. The following regression models are derived for the TDS concentration of the Tigris River in (mg/l).

$$TDS = Q^{-0.255}M^{-0.006}D^{0.694}Y^{0.560} \quad (7)$$

where , M is the month , Y is the year , D is the distance in (km) and Q is the discharge in (m^3/sec) .The correlation coefficient r, RMSE and MAPE are 0.78, 610.4 and 58%, respectively, **Fig.11** .Comparison between results of ANNs and (MLR) analysis showed better results in ANNs model (RMSE and MAPE) values. So, ANNs could explain the variability of the TDS concentration Tigris River more efficiency.

4- CONCLUSIONS

The following conclusions could be deduced from this study

1- ANN performed better than MLR model. The results provided sufficient assessment of performance (r=0.975, RMSE=113.9 and MAPE=11.51%) for ANN model and r=0.78, RMSE=610.4 and MAPE=58% for MLR model.

2- The sensitivity analysis indicated that the distance and discharge have the most significant effect on the predicted TDS concentration, while the year and month have the smallest impact on prediction.

3- ANN's model could be translated into practical formula from which TDS may be calculated. However the predicted formula is important in water quality management and finding the missing data, temporally and spatially.

4- According to the results of ANN model, it is found that the TDS increases with increasing time and distance from upstream, and it is negatively correlated with the flow.

5- The results of this study can be utilized in optimized management and planning of water quality management of the study area in Iraq.

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Table 1. Ranges of variables data used for the ANNs model.

Model Variables	Min. Value	Max. Value
Discharge of river (m^3/sec)	15.0	1949
Distance from upstream (km)	150	1100
Month	1	12
Year	2001	2011
TDS (mg/l)	146	2832

Table 2. Performance of ANNs models for prediction (TDS) of Tigris River.

					Training		Testing		Validation		
Parameter effect	Model No.	Learn Rate	Moment Rate	Hidden layer model number	Correlation Coefficient	RMSE	Correlation Coefficient	RMSE	Correlation Coefficient	RMSE	MAPE for all data (%)
Default Values	1	0.2	0.8	1	0.906	214.6	0.897	497.8	0.838	533.6	32.20
	2	0.2	0.8	2	0.945	170.2	0.863	688.1	0.805	712.2	17.51
	3	0.2	0.8	3	0.952	173.3	0.851	810.7	0.791	831.6	18.49
	4	0.2	0.8	4	0.955	149.8	0.866	690.5	0.824	700.1	13.20
	5	0.2	0.8	5	0.963	137.8	0.880	550.6	0.585	557.2	13.56
	6	0.2	0.8	6	0.963	144.8	0.857	741.89	0.814	752.3	14.49
	7	0.2	0.8	7	0.966	127.38	0.834	873.5	0.789	871.7	12.14
	8	0.2	0.8	8	0.967	124.67	0.846	783.43	0.805	788.11	12.18
	9	0.2	0.8	9	0.968	124.98	0.848	785.5	0.812	782.8	12.18
	10	0.2	0.8	10	0.968	125.79	0.850	777.2	0.809	782.6	12.07
Momentum Rates	11	0.2	0.1	8	0.958	137.7	0.855	685.7	0.808	697.5	11.88
	12	0.2	0.2	8	0.959	137.5	0.854	691.5	0.808	703.9	11.94
	13	0.2	0.3	8	0.959	136.9	0.856	687.8	0.809	701.5	12.02
	14	0.2	0.4	8	0.960	135.9	0.857	684.1	0.811	699.1	12.03
	15	0.2	0.5	8	0.960	134.7	0.857	687.5	0.812	702.7	12.03
	16	0.2	0.6	8	0.961	133.4	0.858	688.7	0.814	702.9	12.24
	17	0.2	0.7	8	0.964	128.7	0.849	744.7	0.805	749.4	12.14
	18	0.2	0.8	8	0.967	124.6	0.896	783.4	0.804	783.1	12.18
	19	0.2	0.9	8	0.970	118.0	0.828	893.1	0.790	884.1	12.07
	20	0.2	0.95	8	0.972	119.0	0.831	907.4	0.787	908.4	12.01
	21	0.1	0.8	8	0.961	133.4	0.895	687.0	0.814	701.1	12.21
	22	0.2	0.8	8	0.967	124.7	0.845	783.4	0.804	783.1	12.18

Learning Rates	23	0.3	0.8	8	0.968	121.4	0.832	863.6	0.791	857.1	12.17
	24	0.4	0.8	8	0.970	118.6	0.829	890.1	0.791	880.8	12.19
	25	0.5	0.8	8	0.970	120.7	0.831	895.9	0.796	880.6	12.96
	26	0.6	0.8	8	0.972	118.6	0.840	852.9	0.8	848.5	12.10
	27	0.7	0.8	8	0.975	113.9	0.869	856.8	0.850	668.1	11.51
	28	0.8	0.8	8	0.975	115.4	0.872	532.6	0.865	563.5	11.87
	29	0.9	0.8	8	0.974	115.4	0.861	402.1	0.894	393.8	12.84
	30	1	0.8	8	0.975	114.6	0.852	394.7	0.916	306.5	12.42

Table 3. Input and output statistics for the ANN model.

Data Set	Statistical Parameter	Month (month)	Year (year)	Distance (m)	Q (m^3/sec)	TDS (mg/l)
Training N=369	Maximum	12	2011	1100	1494	2991
	Minimum	1	2001	150	15	197
	Mean	6.425	2004.91	714.0921	379.8699	726.916
	Sta.dv.	3.452	3.284536	272.078	229.0094	485.3027
Testing N=159	Maximum	12	2011	1100	1582	2877
	Minimum	1	2001	150	22	146
	Mean	6.622	2005.298	592.4528	335.3459	730.1132
	Sta.dv.	3.498	2.696331	399.1759	270.1845	705.6958
Validation N=132	Maximum	12	2011	1100	1360	2986
	Minimum	1	2001	150	36	156
	Mean	6.537	1989.825	588.7925	325.8328	673.3861
	Sta.dv.	3.427	3.342669	409.4047	266.7569	595.345

Table 4. Input and output statistics for the ANN model.

VARIABLE AND DATA SET	t-value	lower critical value	upper critical value	t-test	F-value	lower critical value	upper critical value	F-test
Month								
TESTING	-1.911	-1.975	1.975	Accept	1.579761	1.3001	2.556	Accept
VALIDATION	-1.54856	-1.978	1.978	Accept	0.390277	1.334	2.936	Reject
Year								
TESTING	2.118442	-1.975	1.975	Reject	1.437779	1.3001	2.556	Accept
VALIDATION	1.346531	-1.978	1.978	Accept	1.183871	1.334	2.936	Reject
Distance								

TESTING	-1.42187	-1.975	1.978	Accept	1.584163	1.3001	2.556	Accept
VALIDATION	-1.53378	-1.978	1.975	Accept	1.383798	1.334	2.936	Accept
Discharge								
TESTING	-1.13612	-1.975	1.975	Accept	1.449	1.3001	2.556	Accept
VALIDATION	1.163922	-1.978	1.978	Accept	2.660403	1.334	2.936	Accept
TDS-OUTPUT								
TESTING	1.140016	-1.975	1.975	Accept	1.934	1.3001	2.556	Accept
VALIDATION	1.667779	-1.978	1.978	Accept	1.453	1.334	2.936	Accept

Table 5. Weights and Threshold Levels for the ANN Model.

Hidden layer node	**Wji (weight from node i in the input layer to node j in the hidden layer)**			
	i=4	**i=3**	**i=2**	**i=1**
j=5	-0.326	-3.449	0.773	8.922
j=6	-0.085	-2.203	1.186	-2.373
j=7	-1.287	4.643	6.655	0.752
j=8	-9.527	13.449	2.933	0.989
j=9	-1.455	-5.482	1.356	9.115
j=10	0.372	0.949	-6.637	-1.382
j=11	2.909	-12.493	1.536	-0.409
j=12	0.655	-5.842	3.670	-.1357

Output layer node	Wji (weight from node i in the hidden layer to node j in the output layer)							
	i=12	i=11	i=10	i=9	i=8	i=7	i=6	i=5
j=13	2.570	-2.396	3.062	2.108	8.826	-4.653	-.184	-2.39

Figure 1. Location of the study area.

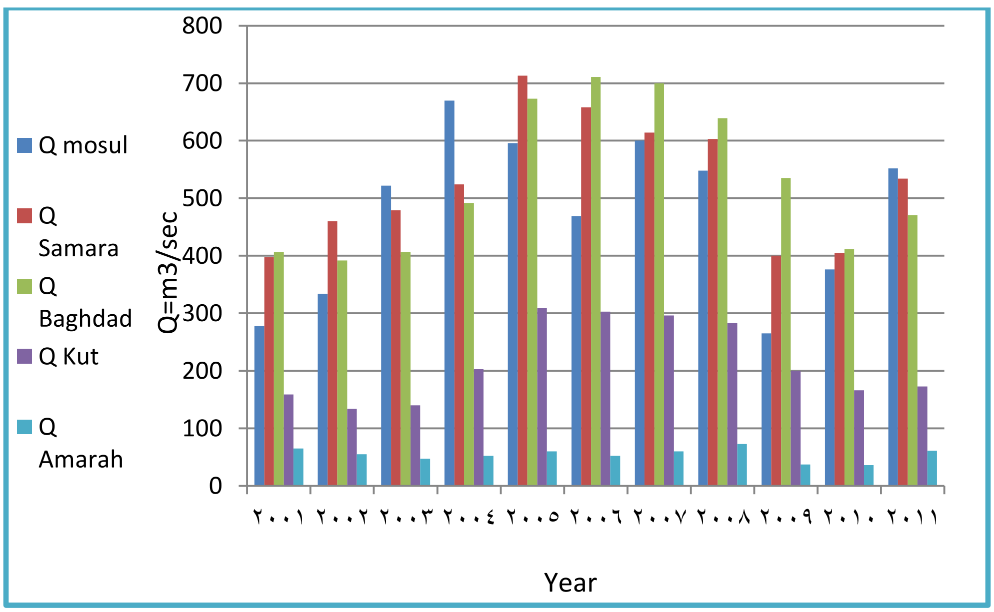

Figure 2. Discharge patterns of selected sites of Tigris river of the period(2001-2011).

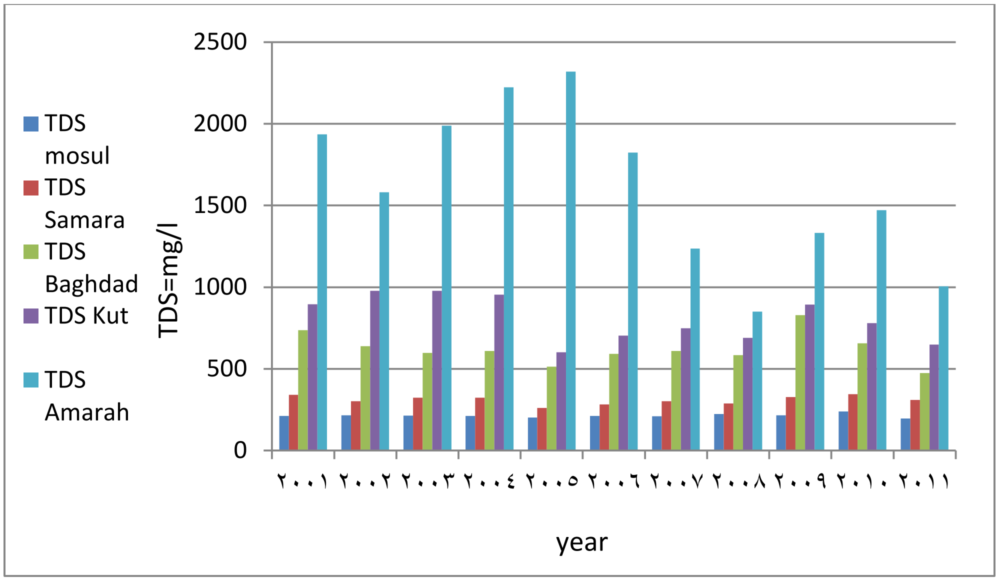

Figure 3. TDS Concentrations patterns of selected sites of Tigris river of the period (2001-2011).

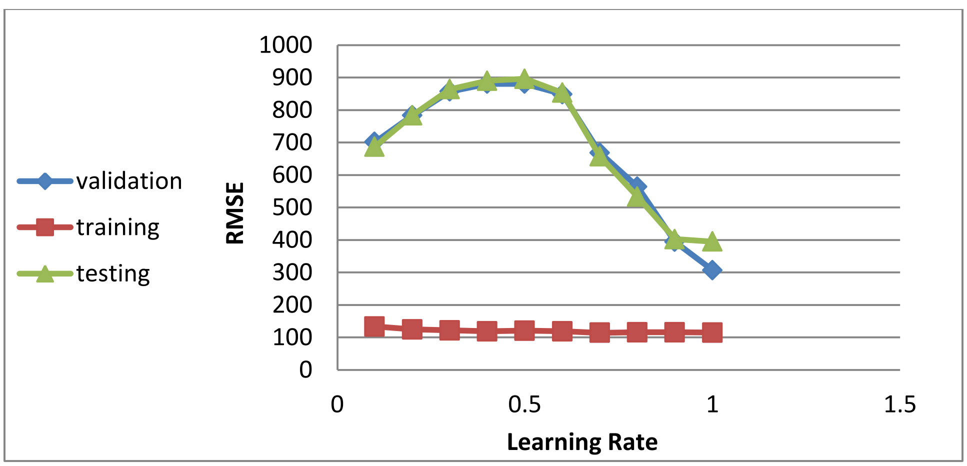

Figure 4. Performance of ANN model with different values of learning rates (β=0.8).

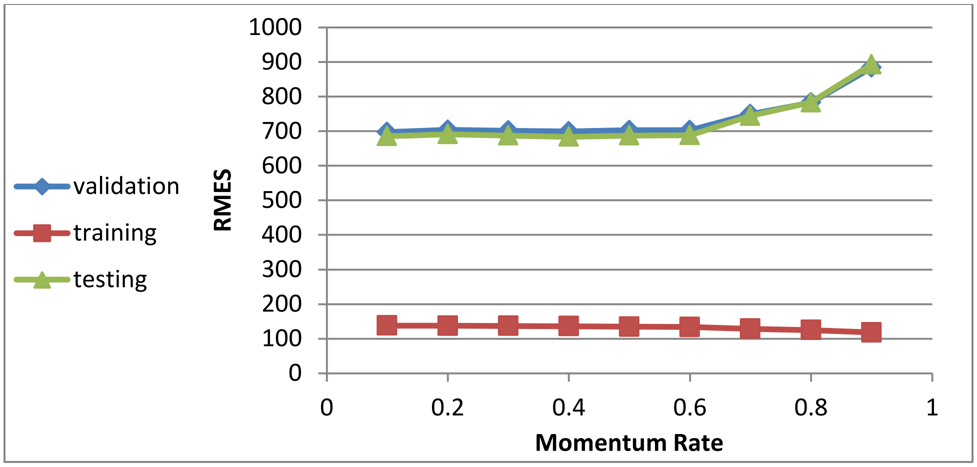

Figure 5. Performance of ANN model with different values of momentum rates,($\alpha = 0.2$).

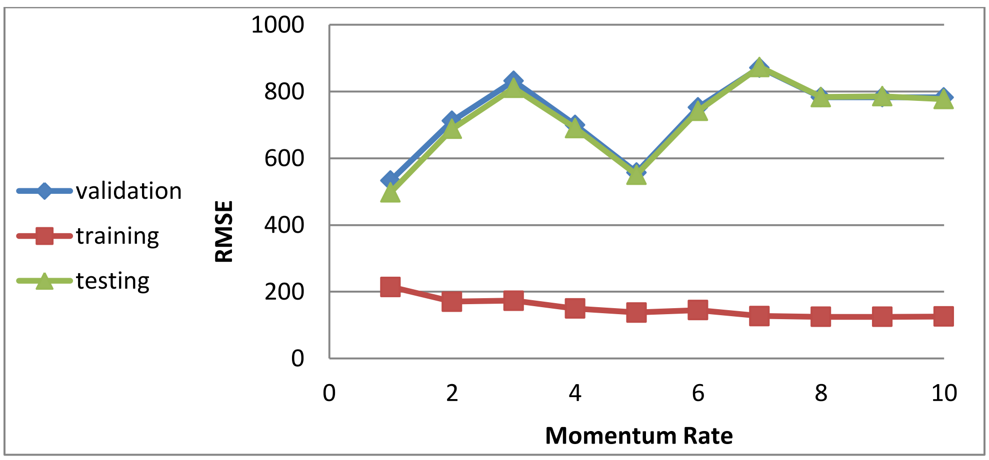

Figure 6. Performance of ANN model with different values of hidden layer nodes,(α=0.2 and β=0.8).

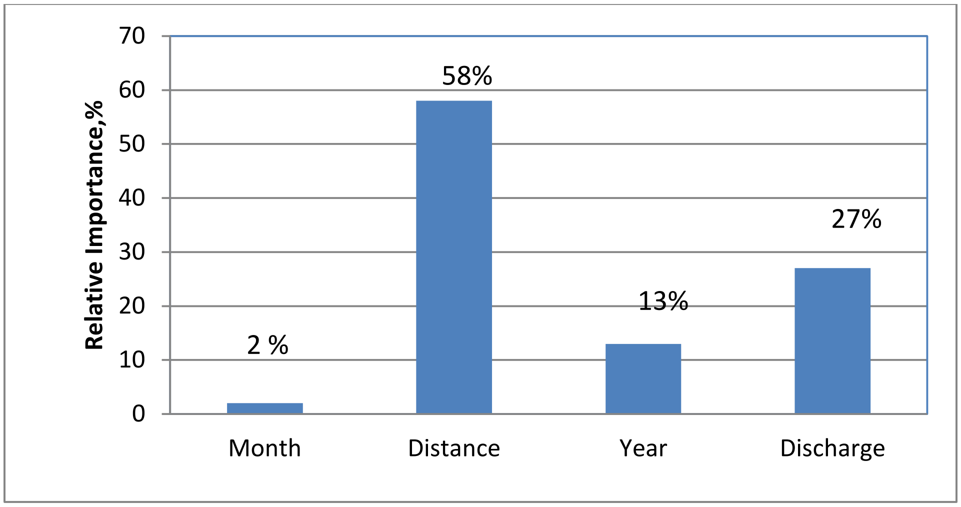

Figure 7. Relative importance of the input variables for the ANN model.

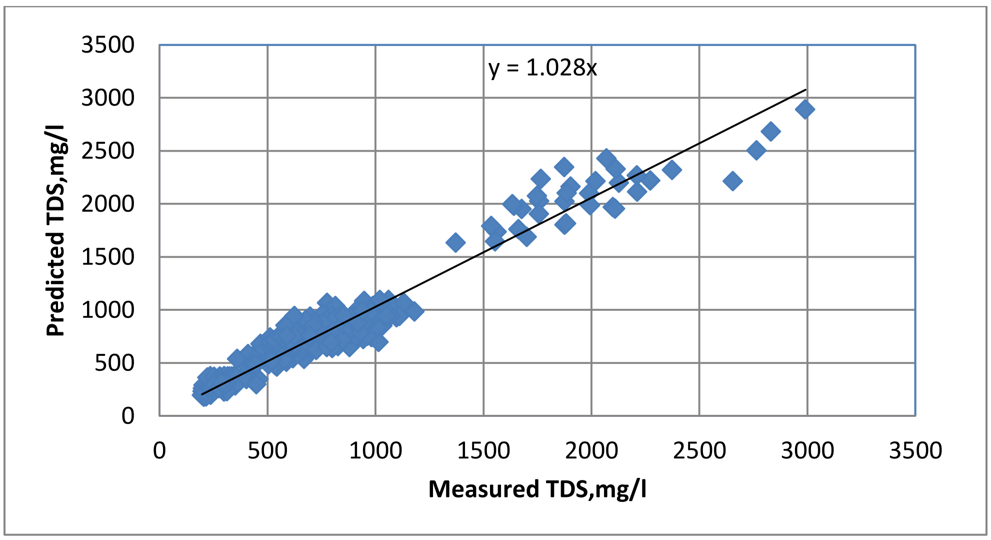

Figure 8. Simulated versus measured valued of TDS concentration of Tigris River.

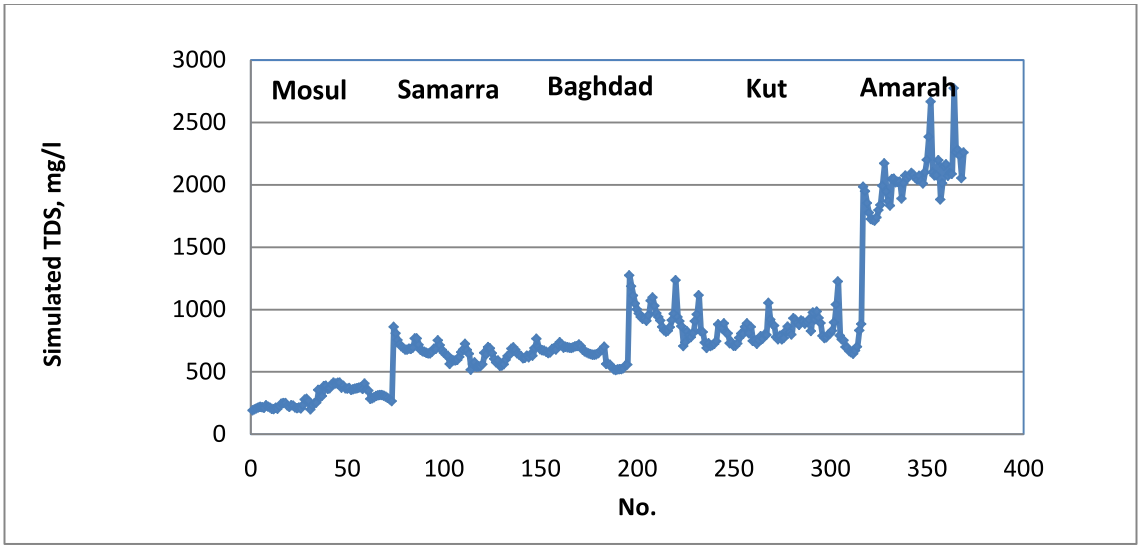

Figure 9. Change of simulated TDS with distance and years, Tigris River.

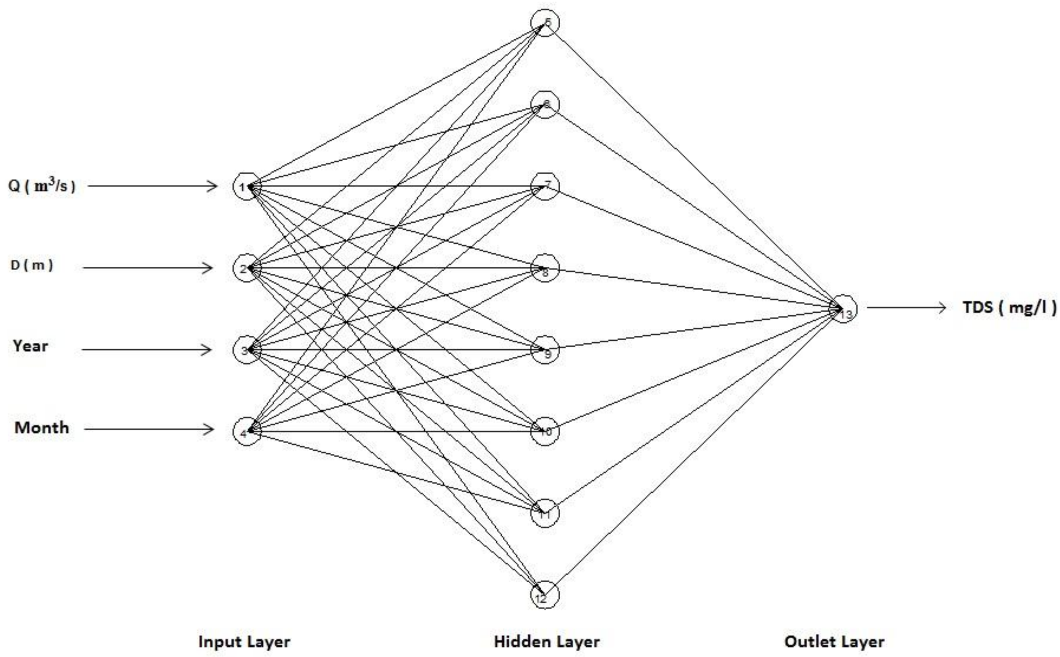

Figure 10. Schematic Representation of the ANN Architecture Model.

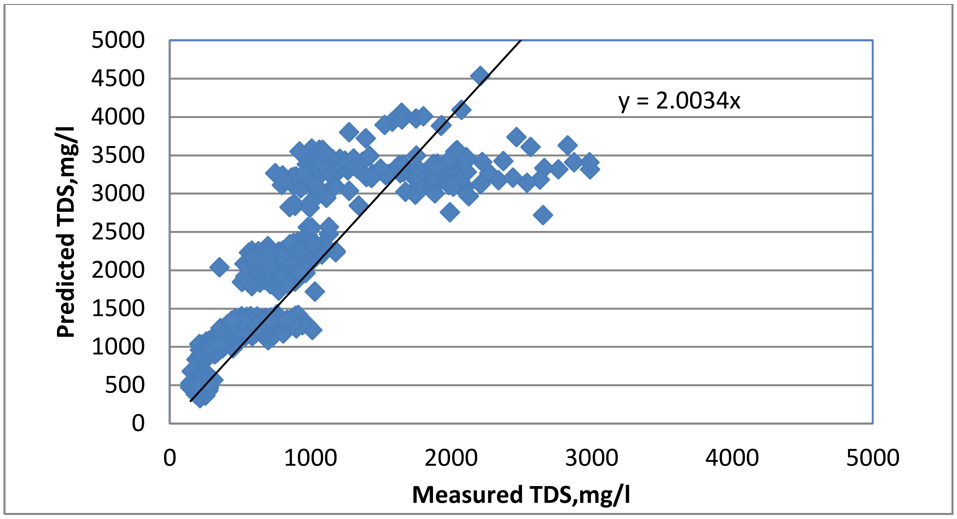

Figure 11. Simulated versus measured values of TDS concentrations for total.